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Emerging local warming signals in observational data

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[1] The global average temperature of the Earth has increased, but year-to-year variability in local climates impedes the identification of clear changes in observations and human experience. For a signal to become obvious in data records or in a human lifetime it needs to be greater than the noise of variability and thereby lead to a significant shift in the distribution of temperature. We show that locations with the largest amount of warming may not display a clear shift in temperature distributions if the local variability is also large. Based on observational data only we demonstrate that large parts of the Earth have experienced a significant local shift towards warmer temperatures in the summer season, particularly at lower latitudes. We also show that these regions are similar to those that are found to be significant in standard detection methods, thus providing an approach to link locally significant changes more closely to impacts. **Citation:** Mahlstein, I., G. Hegerl, and S. Solomon (2012), Emerging local warming signals in observational data, *Geophys. Res. Lett.*, *39*, L21711, doi:10.1029/2012GL053952.

1. Introduction

[2] Changes in temperature and in precipitation have been detected and attributed, at least in part, to human induced increases in greenhouse gases [*Hegerl et al.*, 1997; *Min et al.*, 2008; *Santer et al.*, 1995; *Zhang et al.*, 2006, 2007]. Anthropogenic temperature changes in summer have been detected over many sub-continental regions [*Jones et al.*, 2008] and have changed the probability of hot summers there [*Christidis et al.*, 2012]. Studies have also shown that observed grid point scale temperatures display significant trends over multiple decades similar to those simulated in models [*Karoly and Wu*, 2005]. Detection of a trend in global or regional temperatures, however, does not imply that the change is evident or perceptible for the local living species that have adapted to the prevailing interannual variations over many hundreds of years. One measure of a perceptible change is one in which the local signal is larger than the year-to-year variability, and thus leads to a perceptible shift in the temperature distribution. The signal to noise ratio of warming is an important characteristic of local climates as it seems likely that species become adapted to differences from one year to another, and hence species living in a climate with very small year-to-year variations may be expected to show larger vulnerability. With the important exception of regions heavily affected by the El Niño, lower latitudes display considerably smaller interannual variability than high latitudes and therefore a smaller temperature increase is required for a signal of change to emerge from the background variability [*Hawkins and Sutton*, 2012; *Mahlstein et al.*, 2011]. In this study, the analysis introduced by *Mahlstein et al.* [2011] to examine emerging signals of local warming using climate models is applied to local temperature observations. In our approach, observations are used exclusively, comparing the local distribution between subsequent 30-year segments of summer temperatures.

2. Data and Method

[3] The local observational temperature data set used is the gridded, station-based temperature dataset CRUTEM4 [*Jones et al.*, 2012]. The data are available on a 5 × 5 degree grid, and with (CRUTEM4v) and without (CRUTEM4) variance adjustment for changing numbers of stations used for computing a grid point average. Our analysis uses CRUTEM4, but results were not substantially different using CRUTEM4v. In order to compare our results with other approaches we use control simulations to estimate internal climate variability. These simulations are available from the World Climate Research Program (WCRP) Coupled Model Intercomparison Project Phase 5 (CMIP5) [*Taylor et al.*, 2012].

[4] The three warmest contiguous months are considered to represent summer for each grid point, and are chosen here because they are generally the least variable compared to other seasons. In order to determine whether a specific region shows an emerging warming signal, the following method is used: A base period of 30 years is defined to which future time windows are compared. The future time windows each consist also of 30 years, and are moved at 10-year steps. The base period chosen is 1920–1949, in order to ensure good global data coverage. The analysis ends at the last full decade of the record in 2010. The signal is considered to have emerged when the two windows are significantly different from each other, and this change continues onto future decades. But to further improve data coverage, the test is applied when out of 30 summer values, at least 28 are present in the window, including the base period. If this is not the case, this specific grid cell is not further considered. For each grid cell, the Kolmogorov-Smirnov test checks whether the moving future window is significantly different from the base period in terms of the distribution of their summer temperatures. When this is the case, the signal is considered to have emerged. This test is sensitive to changes in the mean, but it is less sensitive to changes in the tails of the distribution. Thus, in this analysis changes in extremes are less important than

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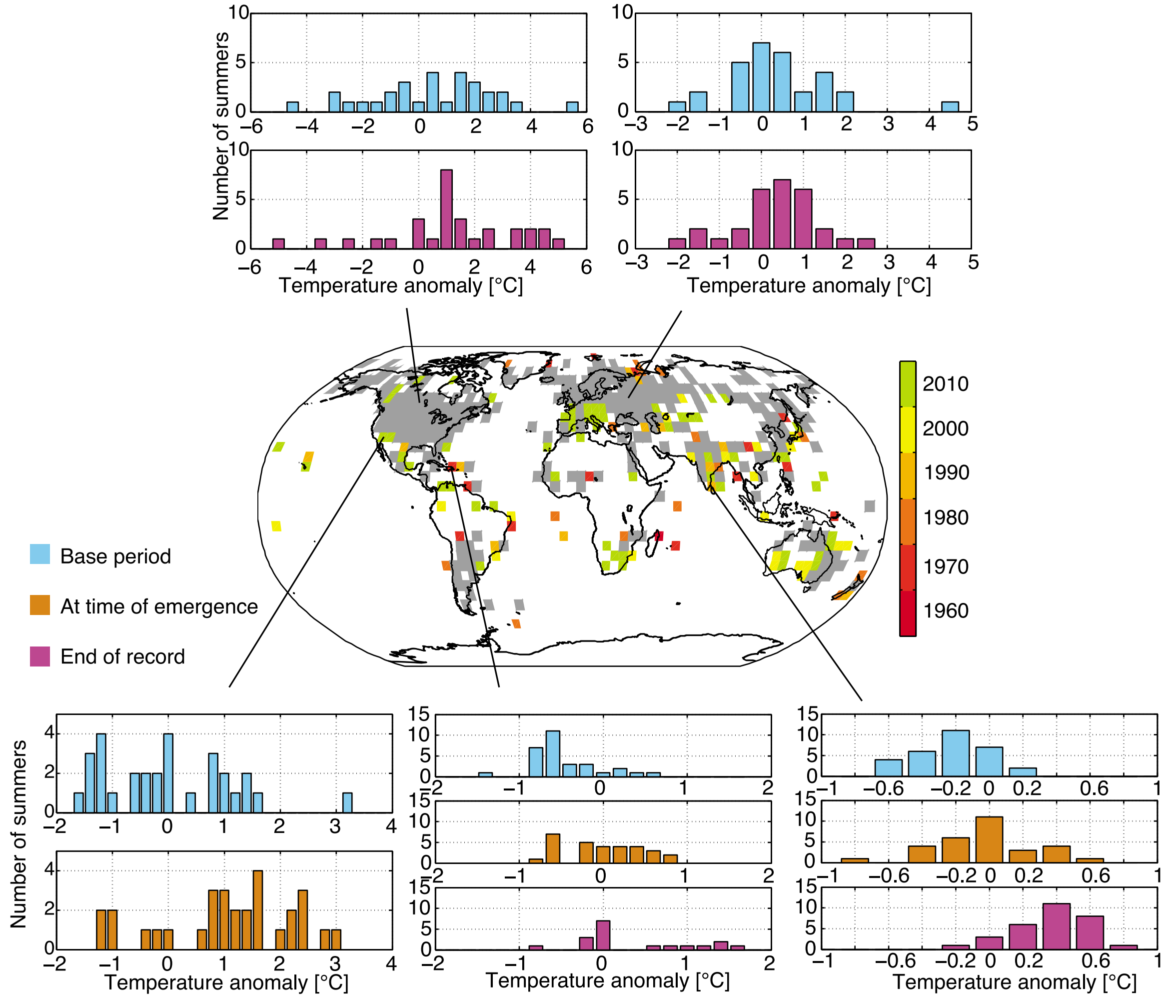

Figure 1. Year of emerging temperature signal (map), grey areas have no emerging signal, white areas contain no data. The year indicates the last year of the 30-year time window. The panels above and below the map show the changes of surface temperature for the indicated grid cells. The blue color represents the temperature distribution during the base period (1920–1949), the orange color the distribution at the time of emergence (see map) and the purple color shows the temperature distribution at the end of the record. If there is no purple color, the year of the emergence is also the end of the record.

changes in the center of the distribution. For details of the statistical method, including its comparison to a number of other statistical approaches, see *Mahlstein et al.* [2011]. In this study there is only one dataset to test, therefore the robustness of the results is an issue. In order to address this, once the signal has emerged in a specific grid cell, the grid cell was further tested in the following decades to ensure that the emergence persists, and in order to reduce the influence of decadal variability on emergence.

3. First Emerging Signal in the 1960's Mainly in Low Latitude Regions

[5] The map in Figure 1 shows the distribution of the year of the emerging temperature signals found. The year shown refers to the last year of the time window in which emergence occurs. Many low latitude regions show a signal that has already emerged or is emerging, whereas the higher latitudes show fewer areas with significant changes on the small-scale. In comparison with the model study [*Mahlstein et al.*, 2011] the results are remarkably similar. Exceptions to this are the relatively early emerging signals in northern Europe and Greenland (for more discussion see below). The histograms in Figure 1 further illustrate the shifts in the surface temperature. The three grid cells depicted below the map clearly illustrate how local extreme warm events have become more common over the past decades in some places, as described by *Schar et al.* [2004] for Europe, and by *Christidis et al.* [2012] for many regions at a larger scale. The two histograms above the map illustrate cases of no emergence of a temperature signal. There appears to be a slight shift towards warmer temperatures at least in one of these latter regions, but the larger interannual variability prevents such a signal from clearly emerging as significant. In general, higher latitude regions have a larger year-to-year local variability than lower latitudes. Therefore, despite the fact that northern high latitudes show larger warming signals, the signal is still not large enough to emerge from the variability.

[6] These results document that for quite large areas (i.e., southern Europe, India, South Africa, northern South America, southern North America, and parts of Australia) summer

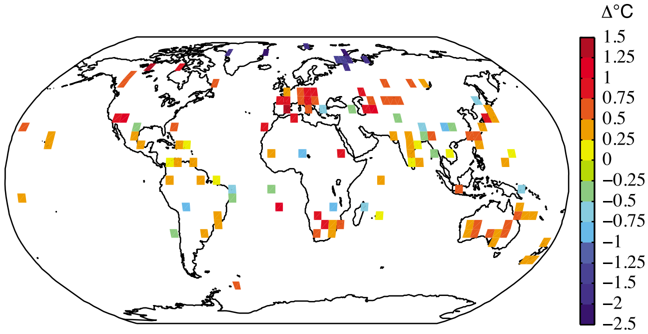

Figure 2. The map shows the difference in the mean summer temperature during the base period and the mean summer temperature of the time window at emerging. The majority of the grid cells show a warming signal, up to 1.5°C. A few grid cells show a change towards cooler temperatures.

season temperatures have increased more than the variability that these regions have experienced in the past, so that significant changes have already happened. About 20% of the extra tropical grid points over land (north and south of 22.5°) with data show emerging signals, while about 40% of the tropical grid points with data show emerging points. This is a far larger number than expected by chance, and the pattern of emergence does not follow known teleconnection patterns, making it highly unlikely that it reflects random spatially connected emergence. Similar to the results based on models [*Mahlstein et al.*, 2011], a large fraction of early emergence occurs in low latitudes, and the pattern of emergence that has been observed is similar to what is expected from climate models. The reason why the low latitudes emerge earlier than others is that the year-to-year variability is lower in this region. While the absolute signal is generally smaller than in higher latitudes, since the interannual differences are small, the signal emerges sooner than in high latitudes where the year-to-year changes are larger. Observational uncertainties exist [*Morice et al.*, 2012] and results may vary using different data sets for observed temperature data. Yet the basic pattern of earlier emergence in low latitudes should remain robust, as interannual variability will be larger in high latitudes in all data sets. The exact year when the signal is emerging may vary for some grid points, and depends on the choice of the base period as well as on the length of the time window. The key point is that significant changes have happened, with earlier changes in the lower latitudes.

[7] However, not every emerging signal in Figure 1 is a warming signal. A number of spots (22.4% of the grid points with emergence) show a significant cold shift. Most spots with a cooling signal have no neighbors. In contrast, for a warming signal the ratio between points with and without neighbors is 3:1. As random errors and inhomogeneities in data should usually be uncorrelated between grid boxes, having a neighbor with the same emerging signal increases confidence that the emergence is due to a changing climate, not due to very small-scale changes or inhomogeneous records. Figure 2 shows the distribution of warming and cooling grid cells. The cooling spots in South America and Africa are very likely based on very few stations. Local land use changes may also be important at some locations. The cooling in some regions of the northern high latitudes emerges very early in the record, and reflects cooling following the very strong warming during the early 20th century [e.g., *Bronnimann*, 2009] that was particularly pronounced in high latitudes adjacent to the North Atlantic. This led to cooling in summer temperature trends from the late 40s to 90s [see also, e.g., *Hegerl et al.*, 1997], and leads to emergence of sustained cooling relative to this warm period in a few grid boxes in the proximity of the North Atlantic.

[8] Previous studies have explored significant changes in surface temperature on a local scale, focusing on trends. In contrast, we aim to link the changes in temperature to impacts. By testing whether two time periods are significantly different from each other, the focus is not only on the trend but also includes variability. When a local temperature regime is moving away from the known climate, thus showing an emerging signal, ecosystems are likely stressed by these changes. The two approaches do not differ greatly from each other as illustrated next. *Karoly and Wu* [2005] assessed where regional surface trends can be detected by testing whether the trend is significantly larger than what can be expected from unforced control runs. Figure 3a compares our emergence of the signal with the approach taken by *Karoly and Wu* [2005]. We fitted 90-year trends to the data at each observed grid point with sufficient coverage, and compared the trend with the 95th percentile (5th percentile) of warming (cooling) trends occurring due to internal variability in model control simulations. Overall the results from both methods agree very well. Most grid cells with an early emergence but no significant trend are cooling signals. However, the later in time the emergence happens, the smaller is the agreement

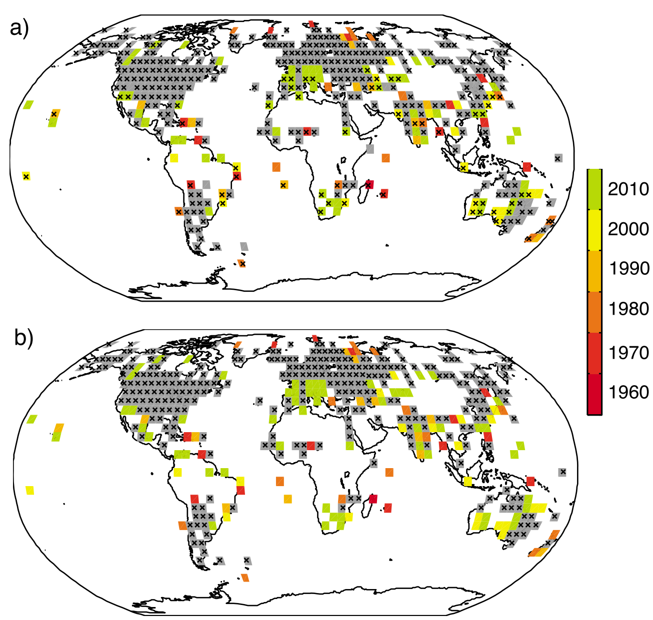

Figure 3. Intercomparison between our approach and a) the detection approach following Karoly and Wu [*Karoly and Wu*, 2005] and b) a signal to noise threshold [*Hawkins and Sutton*, 2012]. Shown in color are the same results as in Figure 1. Hatching means agreement between the two methods; grey and no hatching indicates that the 'other' method shows a (a) significant trend or (b) signal to noise >1; color and no hatching means a significant emergence only in our method but not in the 'other'.

Table 1. Contingency Table Comparing the Method Described by *Karoly and Wu* [2005] and the Method Described Here for Summer Mean Grid Point Temperatures

		Method Described Here	
		Number of Grid Cells with Emergence	Number of Grid Cells With No Emergence
Karoly and Wu [2005]	Number of Grid Cells with Emergence	60	9
	Number of Grid Cells With No Emergence	65	293

with the detection approach, especially for the locations showing an emergence in the last decade of the record. For those points, emergence is due to a recent change that may not be linked to a long-term trend, and illustrates that for our method some recent emerging signals (i.e., that have not yet emerged for multiple decades) might only be due to decadal variability. Table 1 summarizes the results found in Figure 3a. Generally we find fewer points than in *Karoly and Wu* [2005] for both methods. *Karoly and Wu* [2005] used yearly averages in their study which show less variability and have greater long-term changes. Furthermore, some of the more recent generation of the CMIP models have a larger interannual variability compared to their older versions.

[9] We also compared our results to the method introduced by *Hawkins and Sutton* [2012], shown in Figure 3b. Using their method we search for grid cells where the signal of long-term temperature change to interannual climate variability (s/n) is greater than 1 over the 90-year period considered. The noise is derived from control runs in that method as well. Both methods clearly agree only where there is no significant change, as there are no emergences yet with the method of *Hawkins and Sutton* [2012] (Figure 3b) which evaluates when the s/n is larger than one, regardless of how the distribution might have changed. A significant change in the distribution can be expected earlier than a s/n ratio of one, as the trend needs to be quite large in order to achieve this.

4. Conclusions

[10] Our results indicate that detection, attribution, and trend studies alone do not answer the question of whether detected changes are large enough to have a local effect on ecosystems, and whether the changes perceptibly affect the distribution of temperatures. When the temperature increase significantly changes the distribution of year-to-year variability, ecosystems are very likely to be affected by climate change [*Deutsch et al.*, 2008]. This emergence has already happened in a number of regions over land, particularly in the low latitudes. We also show that this emergence of a changing temperature distribution occurs at similar points to those where grid point temperature trends are significant. An advantage of our method is that it does not apply climate model variability, which is uncertain particularly at grid point scales. Temperature so far is the first climate parameter for which this could be shown. Local precipitation changes are not expected to emerge in the near future, mainly because the year-to-year local variability is larger compared to the expected signal [*Mahlstein et al.*, 2012]. However, even if only temperature has significantly changed, some individual species may already be threatened by these changes [*Deutsch et al.*, 2008; *Sinervo*, 2010], and it could result in food insecurity [*Battisti and Naylor*, 2009]. Many of the areas affected are developing countries, which have fewer resources to adapt to these changes and have contributed the least to increased CO_2 emissions.

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